```python
# House Price Prediction using Linear Regression
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
```

```python
# Import the dataset
df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')
```

```python
# Check the shape of the dataset
print(df_train.shape)
print(df_test.shape)
```

```
(1460, 81)
(1459, 80)
```

```python
# Catetorical features
s = (df_train.dtypes == 'object')
object_cols = list(s[s].index)
print("Categorical variables:", object_cols)
print("Number of Categorical variables:", len(object_cols))

# Numerical features
t = (df_train.dtypes == 'int64') | (df_train.dtypes == 'float64')
num_cols = list(t[t].index)
print("Numerical variables:", num_cols)
print("Number of Numerical variables:", len(num_cols))
```

```
Categorical variables: ['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd',
'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual', 'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish',
'GarageQual', 'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature', 'SaleType', 'SaleCondition']
Number of Categorical variables: 43
Numerical variables: ['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea',
'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea',
'MiscVal', 'MoSold', 'YrSold', 'SalePrice']
Number of Numerical variables: 38
```

```python
# data_description.txt
frame_description = open('data_description.txt', 'r')
print(frame_description.read())
frame_description.close()
```

```
MSSubClass: Identifies the type of dwelling involved in the sale.

        20  1-STORY 1946 & NEWER ALL STYLES
        30  1-STORY 1945 & OLDER
        40  1-STORY W/FINISHED ATTIC ALL AGES
        45  1-1/2 STORY - UNFINISHED ALL AGES
        50  1-1/2 STORY FINISHED ALL AGES
        60  2-STORY 1946 & NEWER
        70  2-STORY 1945 & OLDER
        75  2-1/2 STORY ALL AGES
```

```
         80  SPLIT OR MULTI-LEVEL
         85  SPLIT FOYER
         90  DUPLEX - ALL STYLES AND AGES
        120  1-STORY PUD (Planned Unit Development) - 1946 & NEWER
        150  1-1/2 STORY PUD - ALL AGES
        160  2-STORY PUD - 1946 & NEWER
        180  PUD - MULTILEVEL - INCL SPLIT LEV/FOYER
        190  2 FAMILY CONVERSION - ALL STYLES AND AGES

MSZoning: Identifies the general zoning classification of the sale.

       A    Agriculture
       C    Commercial
       FV   Floating Village Residential
       I    Industrial
       RH   Residential High Density
       RL   Residential Low Density
       RP   Residential Low Density Park
       RM   Residential Medium Density

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access to property

       Grvl Gravel
       Pave Paved

Alley: Type of alley access to property

       Grvl Gravel
       Pave Paved
       NA   No alley access

LotShape: General shape of property

       Reg  Regular
       IR1  Slightly irregular
       IR2  Moderately Irregular
       IR3  Irregular

LandContour: Flatness of the property

       Lvl  Near Flat/Level
       Bnk  Banked - Quick and significant rise from street grade to building
       HLS  Hillside - Significant slope from side to side
       Low  Depression

Utilities: Type of utilities available

       AllPub   All public Utilities (E,G,W,& S)
       NoSewr   Electricity, Gas, and Water (Septic Tank)
       NoSeWa   Electricity and Gas Only
       ELO  Electricity only

LotConfig: Lot configuration

       Inside   Inside lot
       Corner   Corner lot
       CulDSac  Cul-de-sac
       FR2  Frontage on 2 sides of property
       FR3  Frontage on 3 sides of property

LandSlope: Slope of property

       Gtl  Gentle slope
       Mod  Moderate Slope
       Sev  Severe Slope

Neighborhood: Physical locations within Ames city limits

       Blmngtn  Bloomington Heights
       Blueste  Bluestem
       BrDale   Briardale
       BrkSide  Brookside
       ClearCr  Clear Creek
```

```
       CollgCr  College Creek
       Crawfor  Crawford
       Edwards  Edwards
       Gilbert  Gilbert
       IDOTRR   Iowa DOT and Rail Road
       MeadowV  Meadow Village
       Mitchel  Mitchell
       Names    North Ames
       NoRidge  Northridge
       NPkVill  Northpark Villa
       NridgHt  Northridge Heights
       NWAmes   Northwest Ames
       OldTown  Old Town
       SWISU    South & West of Iowa State University
       Sawyer   Sawyer
       SawyerW  Sawyer West
       Somerst  Somerset
       StoneBr  Stone Brook
       Timber   Timberland
       Veenker  Veenker

Condition1: Proximity to various conditions

       Artery   Adjacent to arterial street
       Feedr    Adjacent to feeder street
       Norm Normal
       RRNn Within 200' of North-South Railroad
       RRAn Adjacent to North-South Railroad
       PosN Near positive off-site feature--park, greenbelt, etc.
       PosA Adjacent to postive off-site feature
       RRNe Within 200' of East-West Railroad
       RRAe Adjacent to East-West Railroad

Condition2: Proximity to various conditions (if more than one is present)

       Artery   Adjacent to arterial street
       Feedr    Adjacent to feeder street
       Norm Normal
       RRNn Within 200' of North-South Railroad
       RRAn Adjacent to North-South Railroad
       PosN Near positive off-site feature--park, greenbelt, etc.
       PosA Adjacent to postive off-site feature
       RRNe Within 200' of East-West Railroad
       RRAe Adjacent to East-West Railroad

BldgType: Type of dwelling

       1Fam Single-family Detached
       2FmCon   Two-family Conversion; originally built as one-family dwelling
       Duplx    Duplex
       TwnhsE   Townhouse End Unit
       TwnhsI   Townhouse Inside Unit

HouseStyle: Style of dwelling

       1Story   One story
       1.5Fin   One and one-half story: 2nd level finished
       1.5Unf   One and one-half story: 2nd level unfinished
       2Story   Two story
       2.5Fin   Two and one-half story: 2nd level finished
       2.5Unf   Two and one-half story: 2nd level unfinished
       SFoyer   Split Foyer
       SLvl Split Level

OverallQual: Rates the overall material and finish of the house

       10   Very Excellent
       9    Excellent
       8    Very Good
       7    Good
       6    Above Average
       5    Average
       4    Below Average
       3    Fair
       2    Poor
       1    Very Poor
```

```
OverallCond: Rates the overall condition of the house

       10   Very Excellent
       9    Excellent
       8    Very Good
       7    Good
       6    Above Average
       5    Average
       4    Below Average
       3    Fair
       2    Poor
       1    Very Poor

YearBuilt: Original construction date

YearRemodAdd: Remodel date (same as construction date if no remodeling or additions)

RoofStyle: Type of roof

       Flat Flat
       Gable    Gable
       Gambrel  Gabrel (Barn)
       Hip  Hip
       Mansard  Mansard
       Shed Shed

RoofMatl: Roof material

       ClyTile  Clay or Tile
       CompShg  Standard (Composite) Shingle
       Membran  Membrane
       Metal    Metal
       Roll Roll
       Tar&Grv  Gravel & Tar
       WdShake  Wood Shakes
       WdShngl  Wood Shingles

Exterior1st: Exterior covering on house

       AsbShng  Asbestos Shingles
       AsphShn  Asphalt Shingles
       BrkComm  Brick Common
       BrkFace  Brick Face
       CBlock   Cinder Block
       CemntBd  Cement Board
       HdBoard  Hard Board
       ImStucc  Imitation Stucco
       MetalSd  Metal Siding
       Other    Other
       Plywood  Plywood
       PreCast  PreCast
       Stone    Stone
       Stucco   Stucco
       VinylSd  Vinyl Siding
       Wd Sdng  Wood Siding
       WdShing  Wood Shingles

Exterior2nd: Exterior covering on house (if more than one material)

       AsbShng  Asbestos Shingles
       AsphShn  Asphalt Shingles
       BrkComm  Brick Common
       BrkFace  Brick Face
       CBlock   Cinder Block
       CemntBd  Cement Board
       HdBoard  Hard Board
       ImStucc  Imitation Stucco
       MetalSd  Metal Siding
       Other    Other
       Plywood  Plywood
       PreCast  PreCast
       Stone    Stone
       Stucco   Stucco
       VinylSd  Vinyl Siding
       Wd Sdng  Wood Siding
       WdShing  Wood Shingles
```

```
MasVnrType: Masonry veneer type

       BrkCmn   Brick Common
       BrkFace  Brick Face
       CBlock   Cinder Block
       None None
       Stone    Stone

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

       Ex   Excellent
       Gd   Good
       TA   Average/Typical
       Fa   Fair
       Po   Poor

ExterCond: Evaluates the present condition of the material on the exterior

       Ex   Excellent
       Gd   Good
       TA   Average/Typical
       Fa   Fair
       Po   Poor

Foundation: Type of foundation

       BrkTil   Brick & Tile
       CBlock   Cinder Block
       PConc    Poured Contrete
       Slab Slab
       Stone    Stone
       Wood Wood

BsmtQual: Evaluates the height of the basement

       Ex   Excellent (100+ inches)
       Gd   Good (90-99 inches)
       TA   Typical (80-89 inches)
       Fa   Fair (70-79 inches)
       Po   Poor (<70 inches
       NA   No Basement

BsmtCond: Evaluates the general condition of the basement

       Ex   Excellent
       Gd   Good
       TA   Typical - slight dampness allowed
       Fa   Fair - dampness or some cracking or settling
       Po   Poor - Severe cracking, settling, or wetness
       NA   No Basement

BsmtExposure: Refers to walkout or garden level walls

       Gd   Good Exposure
       Av   Average Exposure (split levels or foyers typically score average or above)
       Mn   Mimimum Exposure
       No   No Exposure
       NA   No Basement

BsmtFinType1: Rating of basement finished area

       GLQ  Good Living Quarters
       ALQ  Average Living Quarters
       BLQ  Below Average Living Quarters
       Rec  Average Rec Room
       LwQ  Low Quality
       Unf  Unfinshed
       NA   No Basement

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Rating of basement finished area (if multiple types)

       GLQ  Good Living Quarters
       ALQ  Average Living Quarters
```

```
       BLQ  Below Average Living Quarters
       Rec  Average Rec Room
       LwQ  Low Quality
       Unf  Unfinshed
       NA   No Basement

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

       Floor    Floor Furnace
       GasA Gas forced warm air furnace
       GasW Gas hot water or steam heat
       Grav Gravity furnace
       OthW Hot water or steam heat other than gas
       Wall Wall furnace

HeatingQC: Heating quality and condition

       Ex   Excellent
       Gd   Good
       TA   Average/Typical
       Fa   Fair
       Po   Poor

CentralAir: Central air conditioning

       N    No
       Y    Yes

Electrical: Electrical system

       SBrkr    Standard Circuit Breakers & Romex
       FuseA    Fuse Box over 60 AMP and all Romex wiring (Average)
       FuseF    60 AMP Fuse Box and mostly Romex wiring (Fair)
       FuseP    60 AMP Fuse Box and mostly knob & tube wiring (poor)
       Mix  Mixed

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

Bedroom: Bedrooms above grade (does NOT include basement bedrooms)

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

       Ex   Excellent
       Gd   Good
       TA   Typical/Average
       Fa   Fair
       Po   Poor

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality (Assume typical unless deductions are warranted)

       Typ  Typical Functionality
       Min1 Minor Deductions 1
       Min2 Minor Deductions 2
```

```
       Mod  Moderate Deductions
       Maj1 Major Deductions 1
       Maj2 Major Deductions 2
       Sev  Severely Damaged
       Sal  Salvage only

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

       Ex   Excellent - Exceptional Masonry Fireplace
       Gd   Good - Masonry Fireplace in main level
       TA   Average - Prefabricated Fireplace in main living area or Masonry Fireplace in basement
       Fa   Fair - Prefabricated Fireplace in basement
       Po   Poor - Ben Franklin Stove
       NA   No Fireplace

GarageType: Garage location

       2Types   More than one type of garage
       Attchd   Attached to home
       Basment  Basement Garage
       BuiltIn  Built-In (Garage part of house - typically has room above garage)
       CarPort  Car Port
       Detchd   Detached from home
       NA   No Garage

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

       Fin  Finished
       RFn  Rough Finished
       Unf  Unfinished
       NA   No Garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

       Ex   Excellent
       Gd   Good
       TA   Typical/Average
       Fa   Fair
       Po   Poor
       NA   No Garage

GarageCond: Garage condition

       Ex   Excellent
       Gd   Good
       TA   Typical/Average
       Fa   Fair
       Po   Poor
       NA   No Garage

PavedDrive: Paved driveway

       Y    Paved
       P    Partial Pavement
       N    Dirt/Gravel

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality
```

```
       Ex   Excellent
       Gd   Good
       TA   Average/Typical
       Fa   Fair
       NA   No Pool

Fence: Fence quality

       GdPrv    Good Privacy
       MnPrv    Minimum Privacy
       GdWo Good Wood
       MnWw Minimum Wood/Wire
       NA   No Fence

MiscFeature: Miscellaneous feature not covered in other categories

       Elev Elevator
       Gar2 2nd Garage (if not described in garage section)
       Othr Other
       Shed Shed (over 100 SF)
       TenC Tennis Court
       NA   None

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

       WD   Warranty Deed - Conventional
       CWD  Warranty Deed - Cash
       VWD  Warranty Deed - VA Loan
       New  Home just constructed and sold
       COD  Court Officer Deed/Estate
       Con  Contract 15% Down payment regular terms
       ConLw    Contract Low Down payment and low interest
       ConLI    Contract Low Interest
       ConLD    Contract Low Down
       Oth  Other

SaleCondition: Condition of sale

       Normal   Normal Sale
       Abnorml  Abnormal Sale -  trade, foreclosure, short sale
       AdjLand  Adjoining Land Purchase
       Alloca   Allocation - two linked properties with separate deeds, typically condo with a garage unit
       Family   Sale between family members
       Partial  Home was not completed when last assessed (associated with New Homes)
```

```
# Combine the dataset for preprocessing
df = pd.concat([df_train, df_test], axis=0, sort=False).reset_index(drop=True)
```

```
df.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN

5 rows × 81 columns

```
# Shape of the dataset
print(df.shape)
```

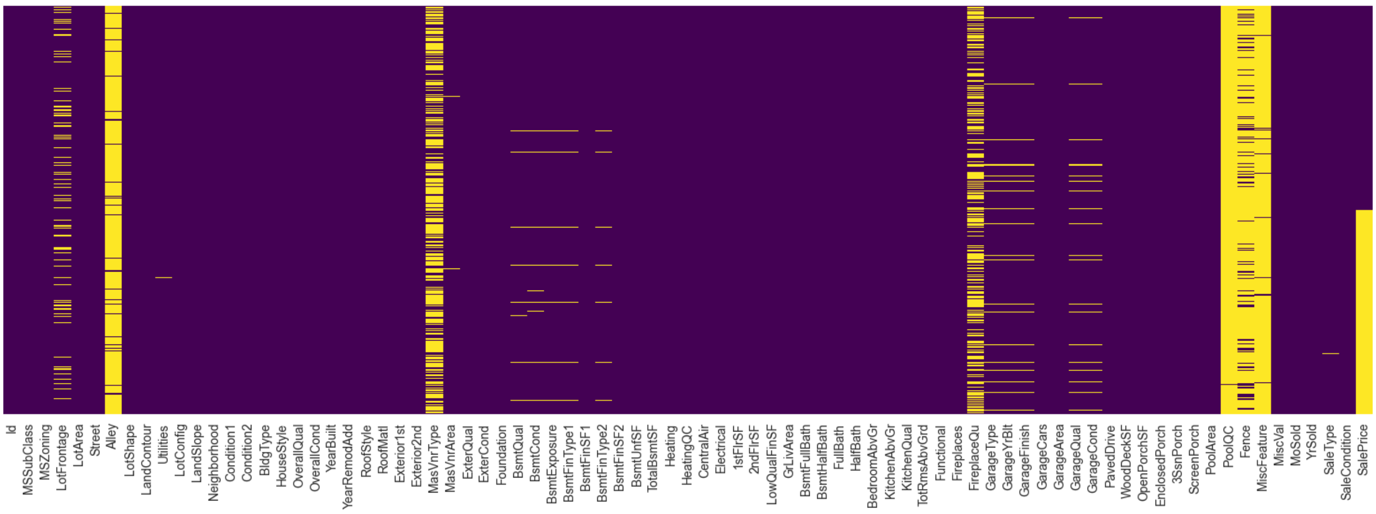
```
(2919, 81)
```

```
# Check the missing values and null values
df.isnull().sum()
```

```
Id                 0
MSSubClass         0
MSZoning           4
LotFrontage      486
LotArea            0
                ...
MoSold             0
YrSold             0
SaleType           1
SaleCondition      0
SalePrice       1459
Length: 81, dtype: int64
```

```
# Heatmap for missing values
plt.figure(figsize=(20, 6))
sns.set_style('dark')
sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap='viridis')
```

```
<Axes: >
```

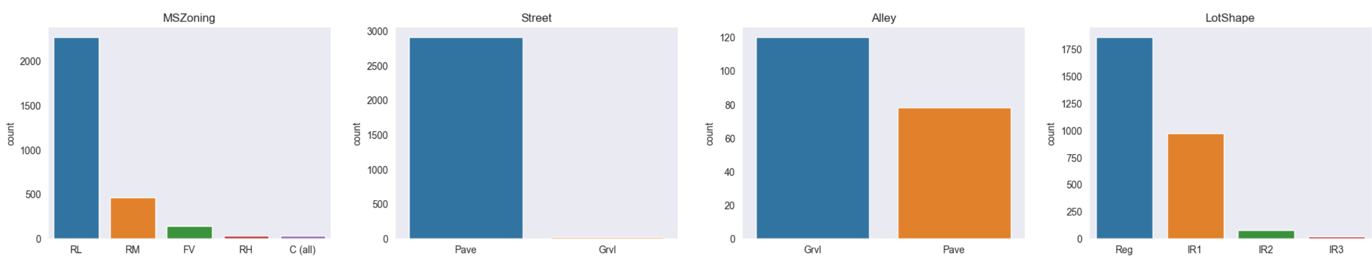



```
# Number of unique values of categorical features
df[object_cols].nunique()
```

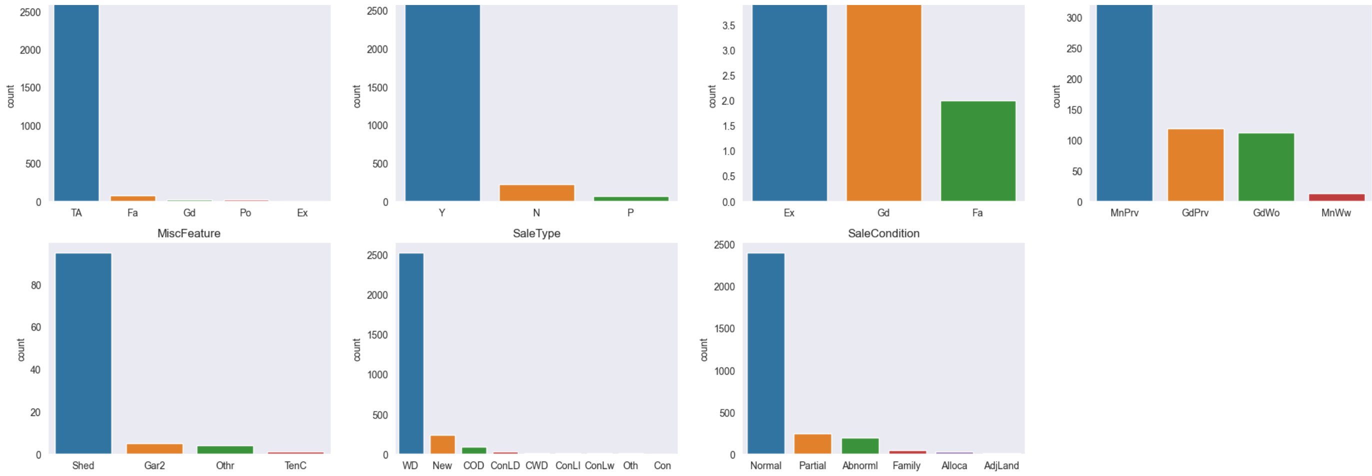
```
MSZoning          5
Street            2
Alley             2
LotShape          4
LandContour       4
Utilities         2
LotConfig         5
LandSlope         3
Neighborhood     25
Condition1        9
Condition2        8
BldgType          5
HouseStyle        8
RoofStyle         6
RoofMatl          8
Exterior1st      15
Exterior2nd      16
MasVnrType        3
ExterQual         4
ExterCond         5
Foundation        6
BsmtQual          4
BsmtCond          4
BsmtExposure      4
BsmtFinType1      6
BsmtFinType2      6
Heating           6
HeatingQC         5
CentralAir        2
Electrical        5
KitchenQual       4
Functional        7
FireplaceQu       5
GarageType        6
GarageFinish      3
GarageQual        5
GarageCond        5
PavedDrive        3
PoolQC            3
Fence             4
MiscFeature       4
SaleType          9
SaleCondition     6
dtype: int64
```

```
# Categorical feature distribution
plt.figure(figsize=(20, 40))
plt.xticks(rotation=90)
cnt = 1
for i in object_cols:
    y = df[i].value_counts()
    plt.subplot(11, 4, cnt)
    sns.barplot(x = list(y.index), y = y)
    plt.title(i)
    cnt += 1
plt.tight_layout()
plt.show()
```

```
C:\Users\anish\AppData\Local\Temp\ipykernel_7032\803961429.py:7: MatplotlibDeprecationWarning: Auto-removal of overlapping axes
is deprecated since 3.6 and will be removed two minor releases later; explicitly call ax.remove() as needed.
  plt.subplot(11, 4, cnt)
```




LandContour
Lvl HLS Bnk Low
Utilities
AllPub NoSeWa
LotConfig
Inside Corner CulDSac FR2 FR3
LandSlope
Gtl Mod Sev
Neighborhood
Condition1
Norm Feedr Artery RRAn PosN RRAe PosA RRNn RRNe
Condition2
Norm Feedr Artery PosN PosA RRNn RRAn RRAe
BldgType
1Fam TwnhsE Duplex Twnhs 2fmCon
HouseStyle
1Story 2Story 1.5Fin SLvl SFoyer 2.5Unf 1.5Unf 2.5Fin
RoofStyle
Gable Hip Gambrel Flat Mansard Shed
RoofMatl
Metal Membran Roll ClyTile
Exterior1st
Exterior2nd
MasVnrType
BrkFace Stone BrkCmn
ExterQual
TA Gd Ex Fa
ExterCond
TA Gd Fa Ex Po
Foundation
PConc CBlock BrkTil Slab Stone Wood
BsmtQual
TA Gd Ex Fa
BsmtCond
TA Gd Fa Po
BsmtExposure
No Av Gd Mn
BsmtFinType1
Unf GLQ ALQ Rec BLQ LwQ
BsmtFinType2
Unf Rec LwQ BLQ ALQ GLQ
Heating
GasA GasW Grav Wall OthW Floor
HeatingQC
Ex TA Gd Fa Po
CentralAir
Y N
Electrical
SBrkr FuseA FuseF FuseP Mix
KitchenQual
TA Gd Ex Fa
Functional
Typ Min2 Min1 Mod Maj1 Maj2 Sev
FireplaceQu
Gd TA Fa Po Ex
GarageType
Attchd Detchd BuiltIn Basment 2Types CarPort
GarageFinish
Unf RFn Fin
GarageQual
TA Fa Gd Po Ex
GarageCond
PavedDrive
PoolQC
Fence
count



Handle the missing values

```
# Drop the features 'Alley', 'Fence', and 'MiscFeature'.
df.drop(['Alley', 'Fence', 'MiscFeature'], axis=1, inplace=True)

# Drop 'Utilities' feature, as all but one have the value 'AllPub'
df['Utilities'].value_counts()
df.drop(['Utilities'], axis=1, inplace=True)

# All entries with missing 'FirePlaceQu' have 'Fireplaces' = 0. Hence fill missing values with 'NA'.
df['FireplaceQu'].fillna('NA', inplace=True)

# Basement features: Fill missing values with 'NA' or '0'.
df['BsmtQual'].fillna('NA', inplace=True)
df['BsmtCond'].fillna('NA', inplace=True)
df['BsmtExposure'].fillna('NA', inplace=True)
df['BsmtFinType1'].fillna('NA', inplace=True)
df['BsmtFinType2'].fillna('NA', inplace=True)
df['BsmtFinSF1'].fillna(0, inplace=True)
df['BsmtFinSF2'].fillna(0, inplace=True)
df['BsmtUnfSF'].fillna(0, inplace=True)
df['TotalBsmtSF'].fillna(0, inplace=True)
df['BsmtFullBath'].fillna(0, inplace=True)
df['BsmtHalfBath'].fillna(0, inplace=True)

# Garage features: Fill missing values with 'NA' or '0'.
df['GarageType'].fillna('NA', inplace=True)
df['GarageYrBlt'].fillna(0, inplace=True)
df['GarageFinish'].fillna('NA', inplace=True)
df['GarageQual'].fillna('NA', inplace=True)
df['GarageCond'].fillna('NA', inplace=True)
df['GarageCars'].fillna(0, inplace=True)
df['GarageArea'].fillna(0, inplace=True)

# Handle missing values with mode
df['MSZoning'].fillna(df['MSZoning'].mode()[0], inplace=True)
df['Exterior1st'].fillna(df['Exterior1st'].mode()[0], inplace=True)
df['Exterior2nd'].fillna(df['Exterior2nd'].mode()[0], inplace=True)
df['MasVnrType'].fillna(df['MasVnrType'].mode()[0], inplace=True)
df['MasVnrArea'].fillna(df['MasVnrArea'].mode()[0], inplace=True)
df['Electrical'].fillna(df['Electrical'].mode()[0], inplace=True)
df['KitchenQual'].fillna(df['KitchenQual'].mode()[0], inplace=True)
df['Functional'].fillna(df['Functional'].mode()[0], inplace=True)
```

```
# Handle missing values with mean
df['LotFrontage'].fillna(df['LotFrontage'].mean(), inplace=True)
```

```
# Handle missing values of 'SaleType' with mode
df['SaleType'].fillna(df['SaleType'].mode()[0], inplace=True)
```

```
# Check the missing values and null values
df.isnull().sum()
```

```
Id                0
MSSubClass        0
MSZoning          0
LotFrontage       0
LotArea           0
                 ...
MoSold            0
YrSold            0
SaleType          0
SaleCondition     0
SalePrice      1459
Length: 77, dtype: int64
```

```
# Drop the features 'Id' and 'SalePrice'
df.drop(['Id', 'SalePrice'], axis=1, inplace=True)
```

```
df.isnull().sum().sum()
```

```
2909
```

```
# Show the features with missing values
df.columns[df.isnull().any()]
```

```
Index(['PoolQC'], dtype='object')
```

```
# All but one entries with missing 'PoolQC' value have 'PoolArea' = 0. Use mode for missing value with non-zero PoolArea. Use 'NA' for the rest of the entries.
df['PoolQC'].fillna('NA', inplace=True)
df['PoolQC'].value_counts()
df.loc[(df['PoolQC'] == 'NA') & (df['PoolArea'] > 0), 'PoolQC'] = df['PoolQC'].mode()[0]
```

```
df.isnull().sum().sum()
```

```
0
```

```
df.shape
```

```
(2919, 75)
```

Data Preprocessing

```
from sklearn.preprocessing import OneHotEncoder
```

```
# Number of categorical features
s = (df.dtypes == 'object')
object_cols = list(s[s].index)
print("Categorical variables:", object_cols)
print("Number of Categorical variables:", len(object_cols))
```

```
Categorical variables: ['MSZoning', 'Street', 'LotShape', 'LandContour', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual', 'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond', 'PavedDrive', 'PoolQC', 'SaleType', 'SaleCondition']
Number of Categorical variables: 39
```

```
# One-hot encoding
OH_encoder = OneHotEncoder(sparse=False)
OH_cols = pd.DataFrame(OH_encoder.fit_transform(df[object_cols]))
OH_cols.index = df.index
OH_cols.columns = OH_encoder.get_feature_names_out(object_cols)
df_final = df.drop(object_cols, axis=1)
df_final = pd.concat([df_final, OH_cols], axis=1)
```

```
C:\Users\anish\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\sklearn\preprocessing\_encoders.py:972: FutureWarning: `sparse` was renamed to `sparse_output` in version 1.2 and will be removed in 1.4. `sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

```
df_final.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	...	S
0	60	65.0	8450	7	5	2003	2003	196.0	706.0	0.0	...	0
1	20	80.0	9600	6	8	1976	1976	0.0	978.0	0.0	...	0
2	60	68.0	11250	7	5	2001	2002	162.0	486.0	0.0	...	0
3	70	60.0	9550	7	5	1915	1970	0.0	216.0	0.0	...	0
4	60	84.0	14260	8	5	2000	2000	350.0	655.0	0.0	...	0

5 rows × 286 columns

```
# Check the data types of the features after one-hot encoding and return the number of features of each data type
df_final.dtypes.value_counts()
```

```
float64    261
int64       25
Name: count, dtype: int64
```

```
df.dtypes[df.dtypes != df.dtypes.iloc[0]]
```

```
MSZoning          object
LotFrontage      float64
Street            object
LotShape          object
LandContour       object
LotConfig         object
LandSlope         object
Neighborhood      object
```

```
Condition1        object
Condition2        object
BldgType          object
HouseStyle        object
RoofStyle         object
RoofMatl          object
Exterior1st       object
Exterior2nd       object
MasVnrType        object
MasVnrArea       float64
ExterQual         object
ExterCond         object
Foundation        object
BsmtQual          object
BsmtCond          object
BsmtExposure      object
BsmtFinType1      object
BsmtFinSF1       float64
BsmtFinType2      object
BsmtFinSF2       float64
BsmtUnfSF        float64
TotalBsmtSF      float64
Heating           object
HeatingQC         object
CentralAir        object
Electrical        object
BsmtFullBath     float64
BsmtHalfBath     float64
KitchenQual       object
Functional        object
FireplaceQu       object
GarageType        object
GarageYrBlt      float64
GarageFinish      object
GarageCars       float64
GarageArea       float64
GarageQual        object
GarageCond        object
PavedDrive        object
PoolQC            object
SaleType          object
SaleCondition     object
dtype: object
```

```
# Check if the shape is consistent
print(df.shape)
print(df_final.shape)
print(df_train.shape)
print(df_test.shape)
```

```
(2919, 75)
(2919, 286)
(1460, 81)
(1459, 80)
```

```
# Split the dataset into train and test
X_train = df_final.iloc[:1460, :]
X_test = df_final.iloc[1460:, :]
y_train = df_train['SalePrice']
```

```
# Check the consistency of the split
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
```

```
(1460, 286)
(1459, 286)
```

```
(1460,)
```

```
# Split the train dataset into train and validation
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2, random_state=0)
```

Model Building

Linear Regression

```
# Linear Regression
reg = LinearRegression()
reg.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
from sklearn.metrics import mean_absolute_error
```

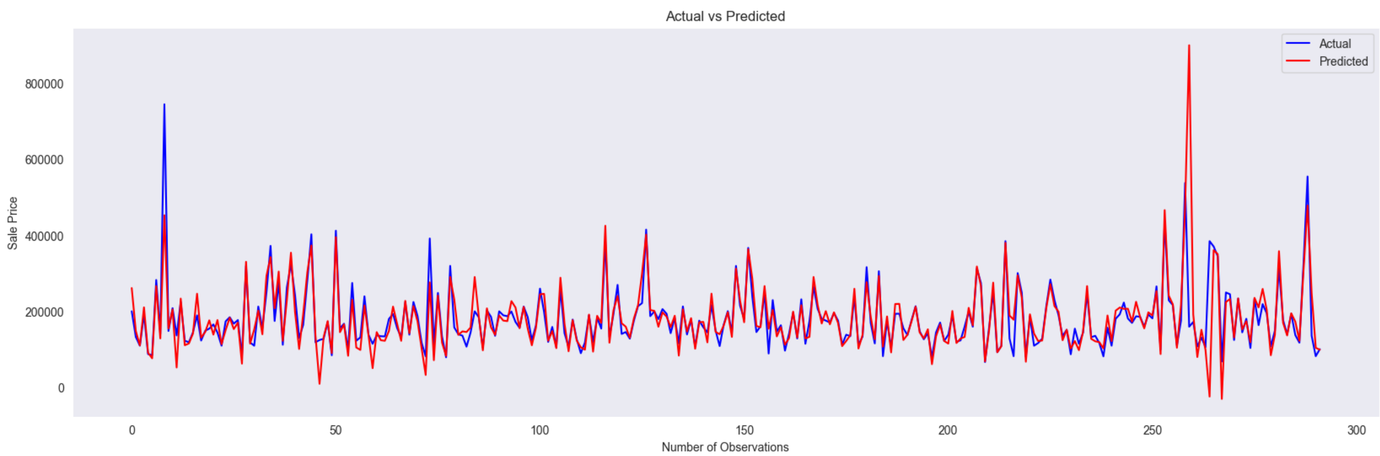
```
# Predict the validation set
y_pred = reg.predict(X_val)

# The mean squared error
print('Mean squared error: %.2f' % mean_squared_error(y_val, y_pred))

# The mean absolute error
print('Mean absolute error: %.2f' % mean_absolute_error(y_val, y_pred))
```

```
Mean squared error: 3450893903.48
Mean absolute error: 22874.61
```

```
# Plot the predicted values against the actual values
plt.figure(figsize=(20, 6))
plt.plot(y_val.values, color='blue', label='Actual')
plt.plot(y_pred, color='red', label='Predicted')
plt.title('Actual vs Predicted')
plt.xlabel('Number of Observations')
plt.ylabel('Sale Price')
plt.legend()
plt.show()
```




```
# Scatter plot of the predicted values against the actual values
plt.figure(figsize=(20, 6))
```

```
plt.scatter(y_val.values, y_pred, color='blue')
plt.title('Actual vs Predicted')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.show()
```